5th International Symposium of Biofumigation 9-12 September 2014

Natacha MOTISI

cirad
AGRICULTURAL RESEARCH FOR DEVELOPMENT

Melen LECLERC

INRA
SCIENCE & IMPACT

Dealing with the variability in biofumigation efficiency through epidemiological modelling

UNIVERSITY OF CAMBRIDGE

INSTITUT TECHNIQUE DE LA BETTERAVE
ITB

Plan

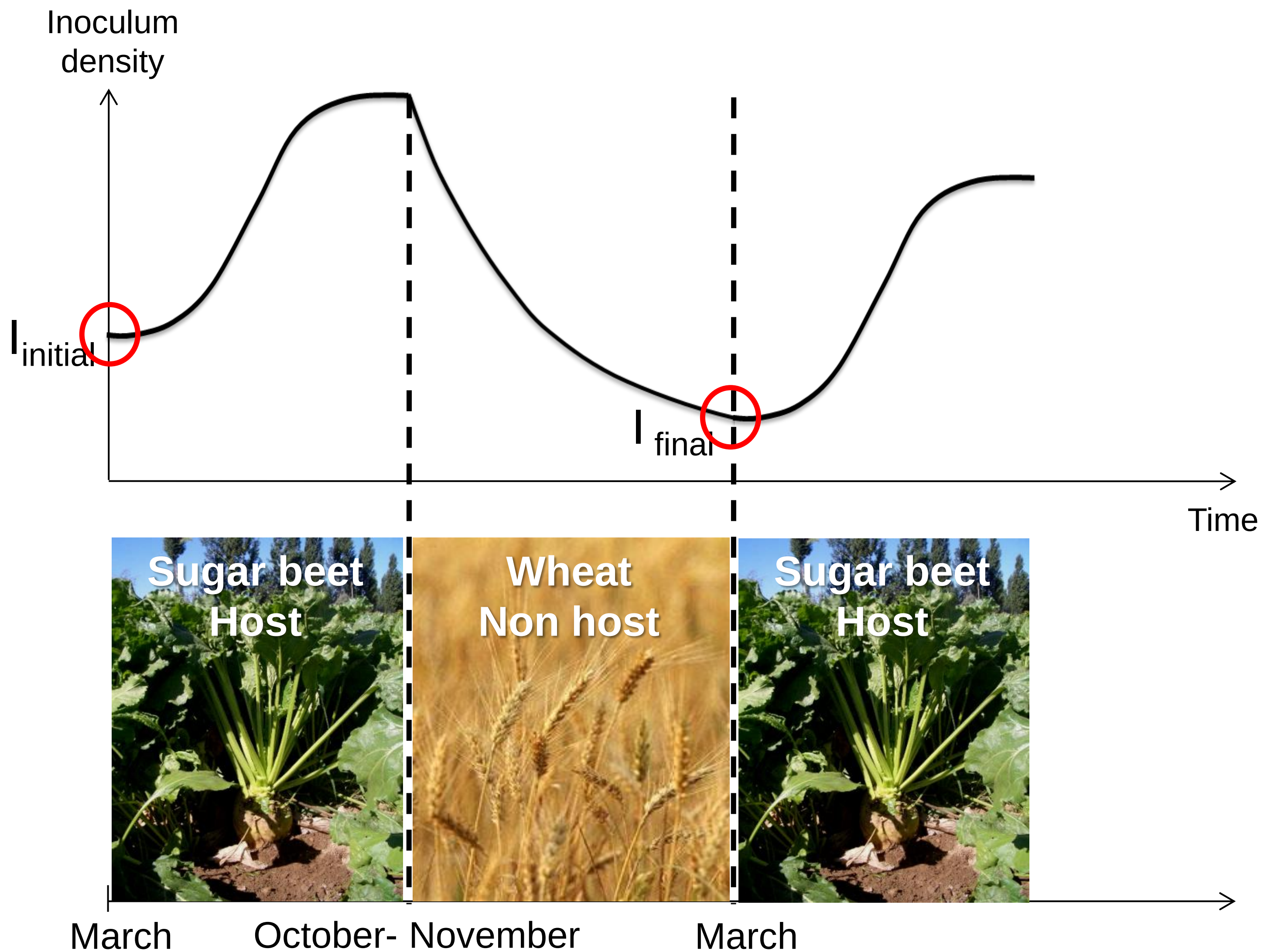
I. Modes of action of a biofumigant crop

II. Objectives

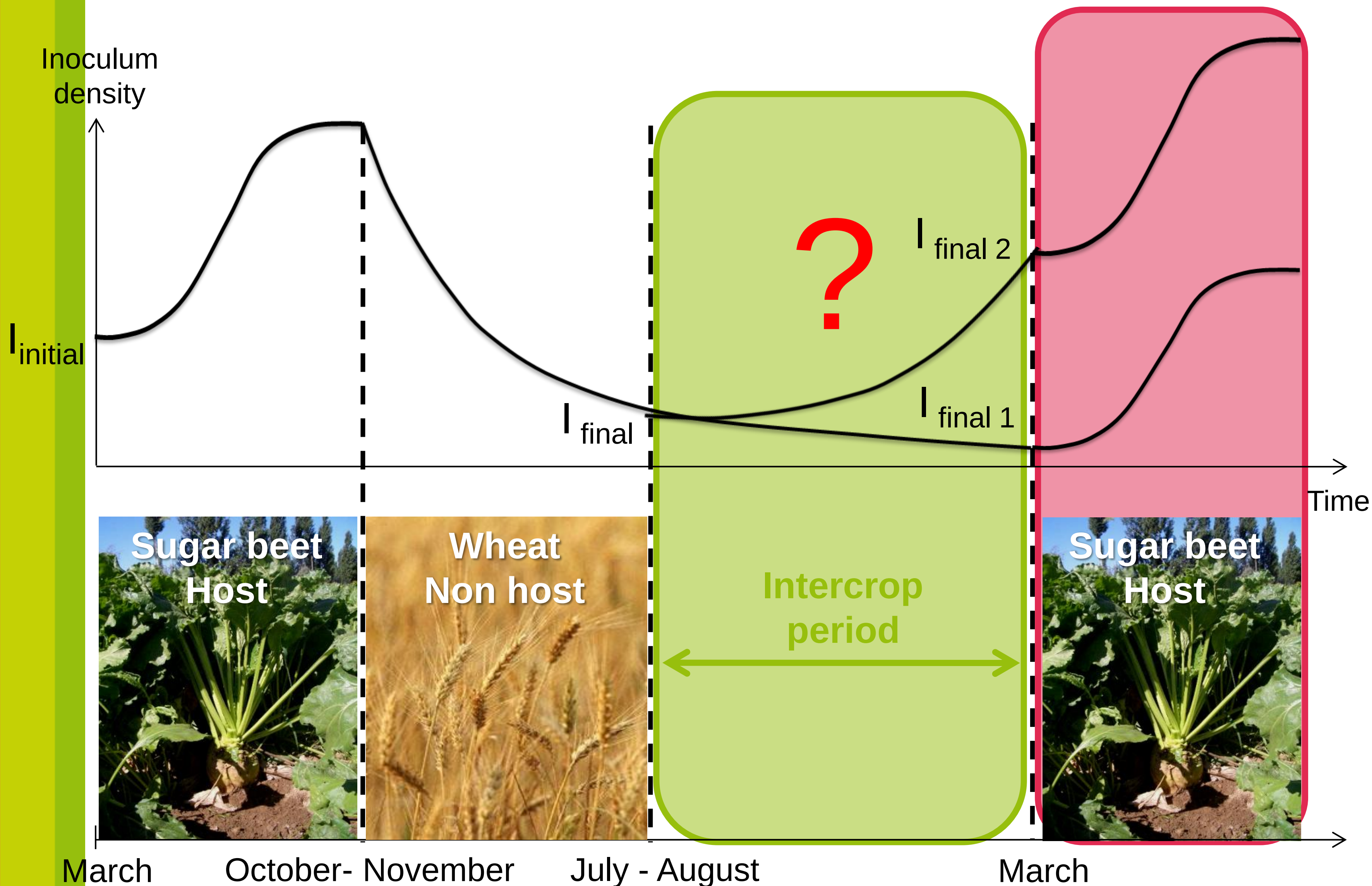
III. Experiments

IV. Modelling
   a. Temporal modelling with a simple mechanistic model
   b. Spatially explicit model

Managing soilborne diseases by diversifying crops in the rotation



The intercrop period : action on soil inoculum reservoir



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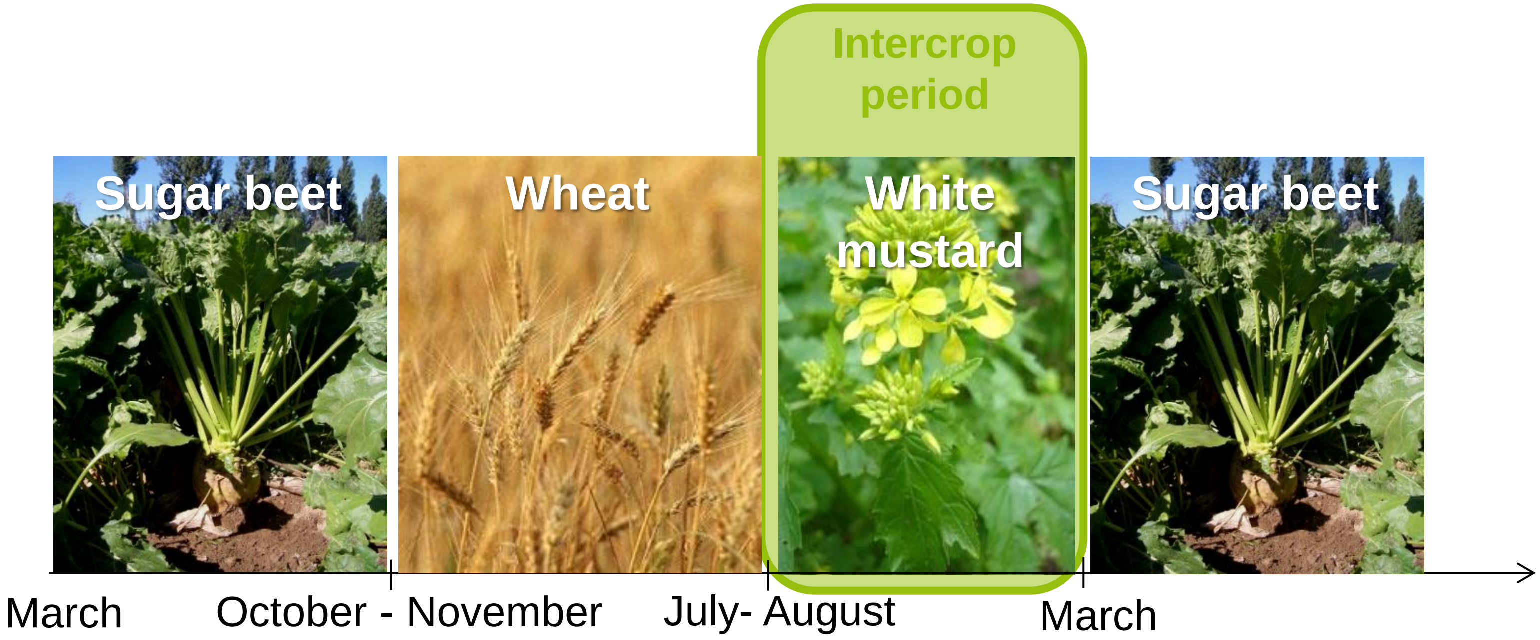
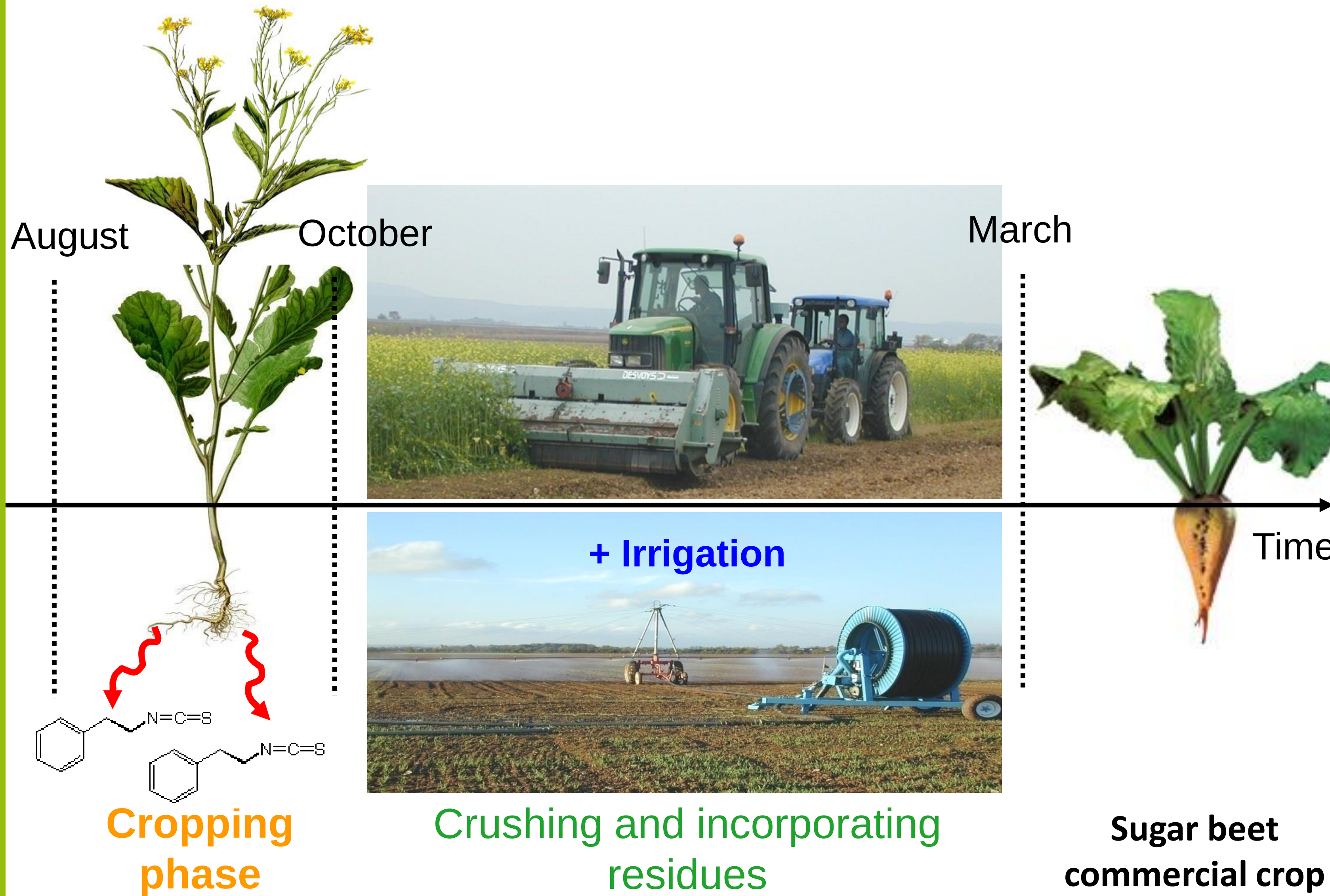
Managing the intercrop period



Allelopathic properties of Brassica intercrops

Set up of the biofumigation technics



Biofumigation efficiency after incorporation of Brassica residues – extract from Motisi *et al.* (2010)

	Gaeumannomyces graminis var. *tritici*	*Rhizoctonia solani*	*Fusarium sp.*	*Verticillium dahliae*
Davis *et al.*, 1996				+
Hartz *et al.*, 2005			-	0
Kirkegaard *et al.*, 2004			+	
Stephens *et al.*, 1999		0	0	
Gardner *et al.*, 1998	+ -			
Kirkegaard *et al.*, 2000	0			
van Os *et al.*, 2002		0		
Little *et al.*, 2004		0		
Larkin *et al.*, 2007		+ 0		
Njoroge *et al.*, 2008			0	
Snapp *et al.*, 2007		+		

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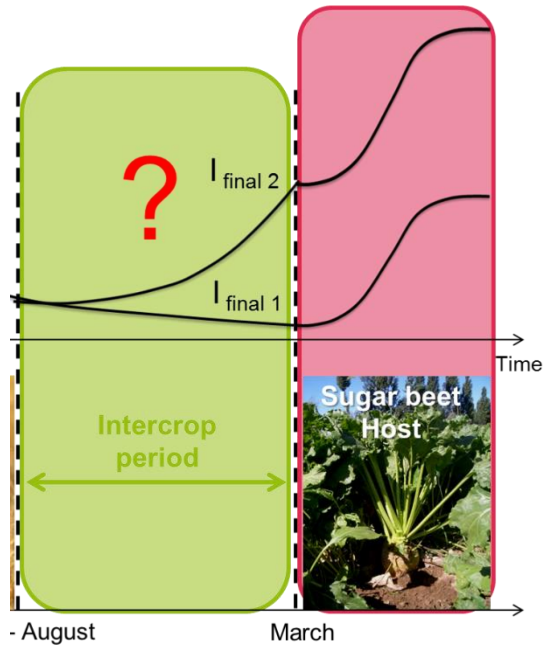
Using an epidemiological framework

- To explain the action of biofumigant crops on soilborne **diseases dynamics** and **epidemiological mechanisms**



- To understand how biofumigation affects the **variability of epidemics** and, thus, how it impacts the **uncertainty of the spread of disease** in field conditions

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How?

- Field experiment
  - By disentangling the mechanisms of biofumigation

Partial biofumigation

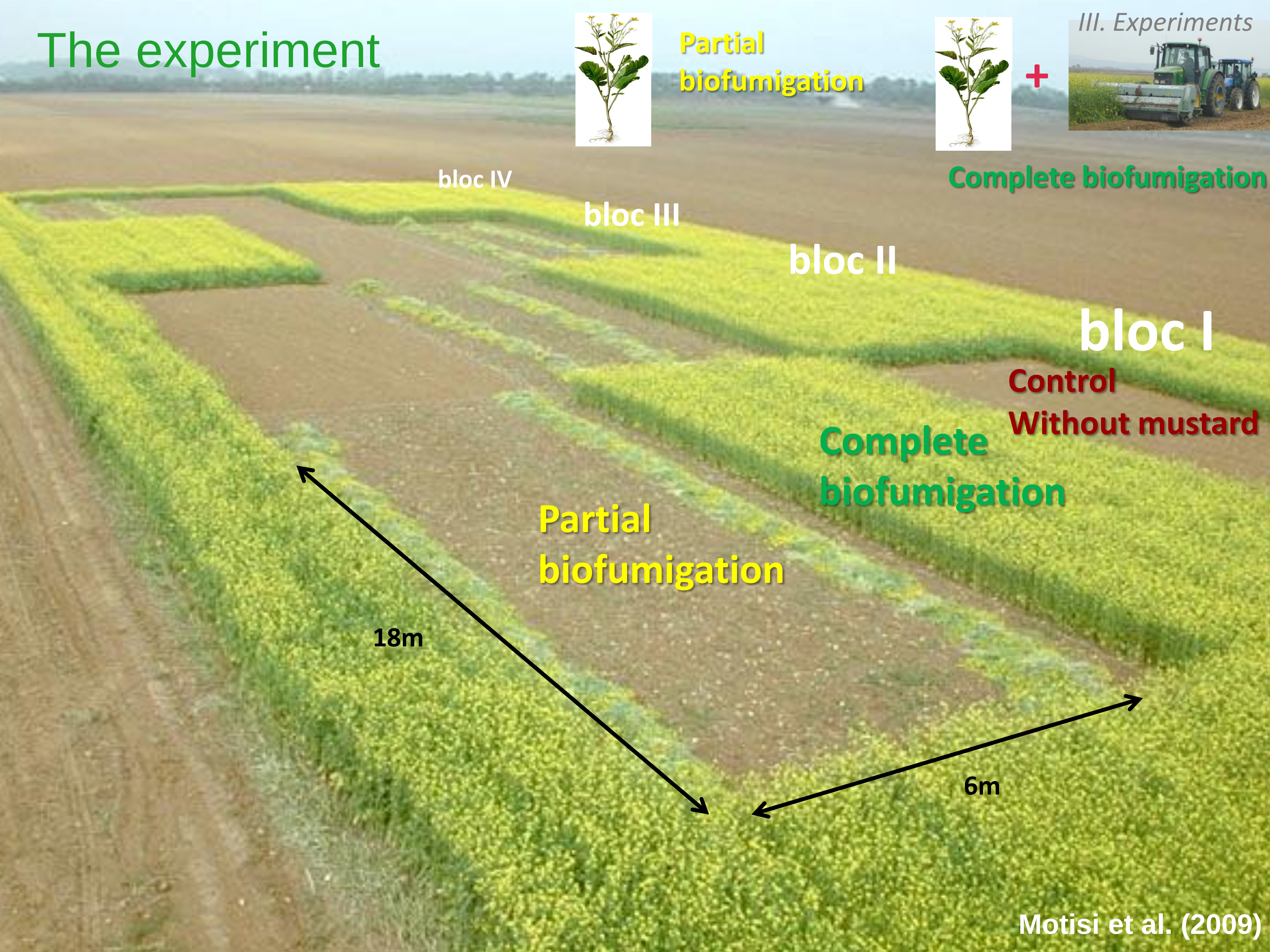
\+

Complete biofumigation

  - By monitoring disease spread over time

- Modelling
  - Temporal mechanistic model
  - Spatio-temporal model

The experiment



The pathosystem

Above ground

Visible epidemic: wilted plants

Non destructive sampling

Hidden epidemic: cryptic infections

Destructive sampling

Below ground

Tracking epidemic progression in the field

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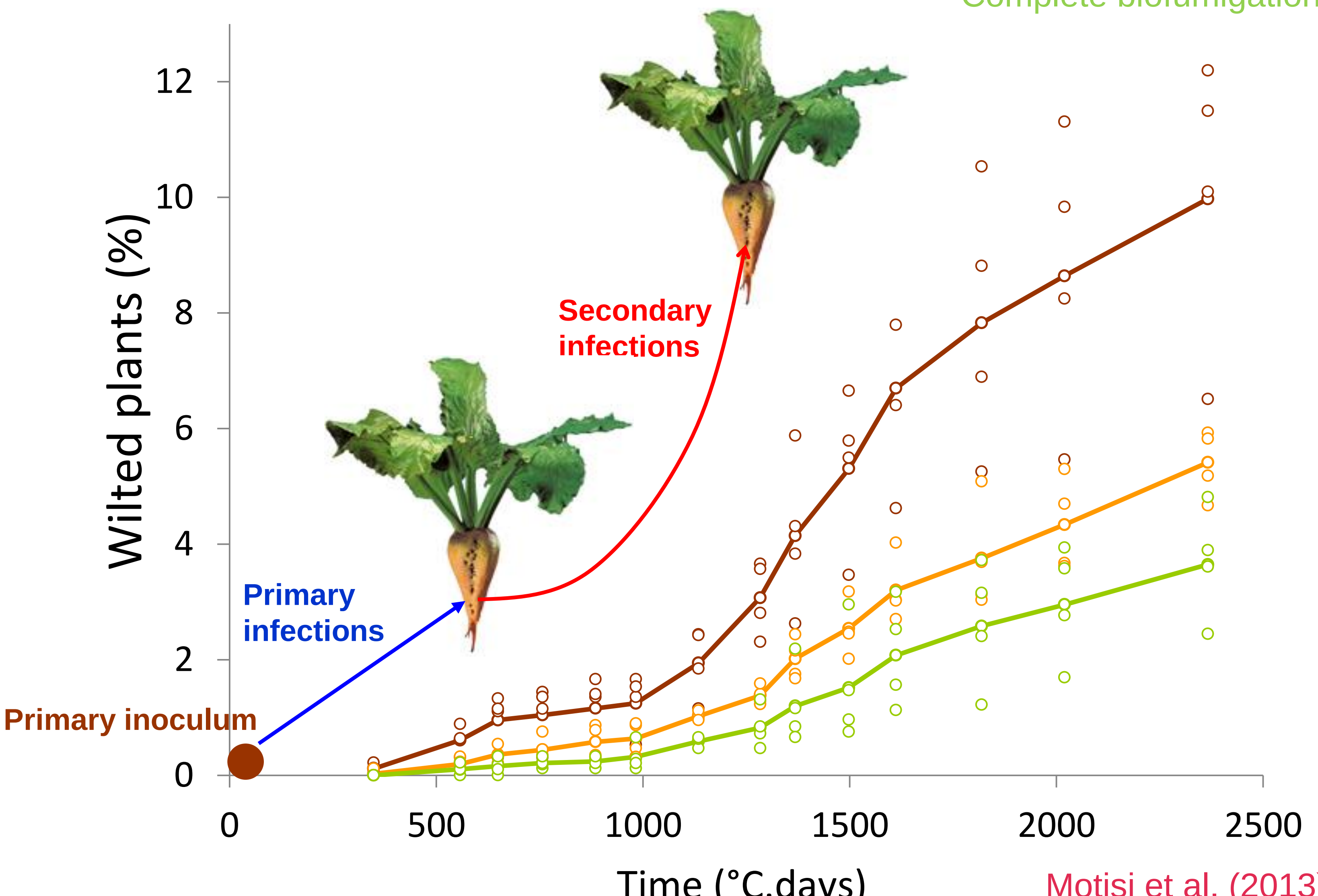
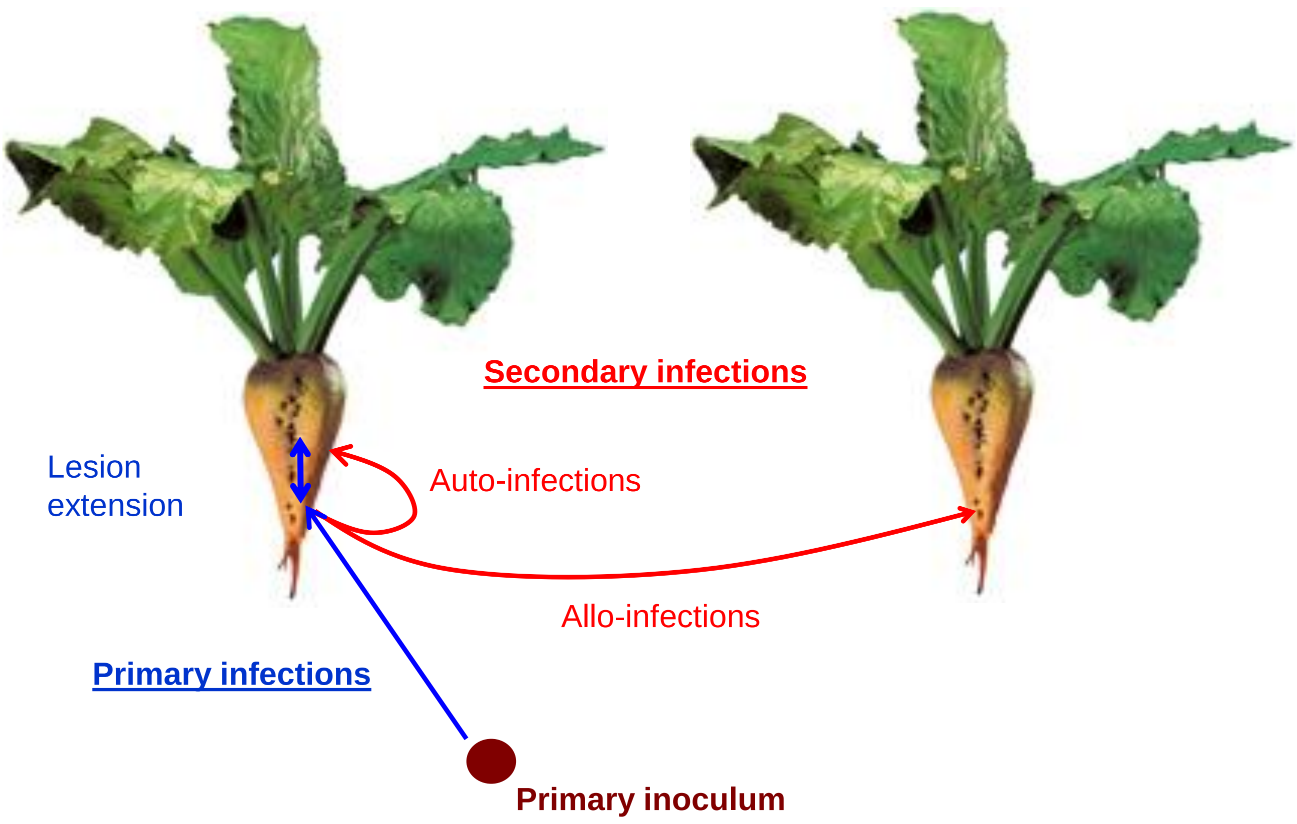
Initial inspection of the disease progress curves



Motisi et al. (2013)

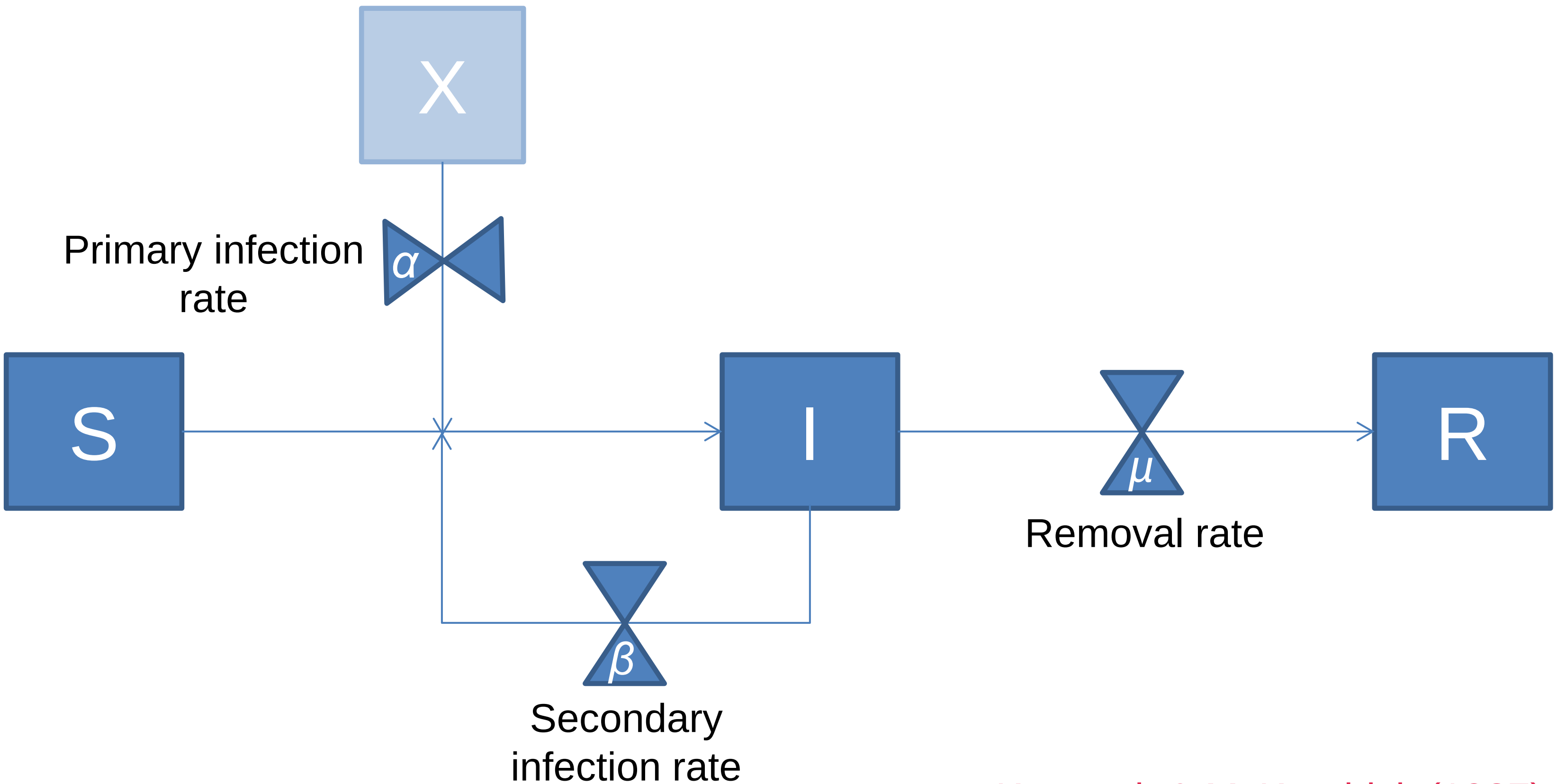
Considering the dynamics of the pathogen to be controlled

Rhizoctonia solani on sugar beet



General modelling approach
Temporal dynamics

SIR model
(Susceptible – Infected – Removed)



Kermack & McKendrick (1927)
Van der Plank (1963)

Adapting the SIR model to our pathosystem

SID model

Susceptible plants

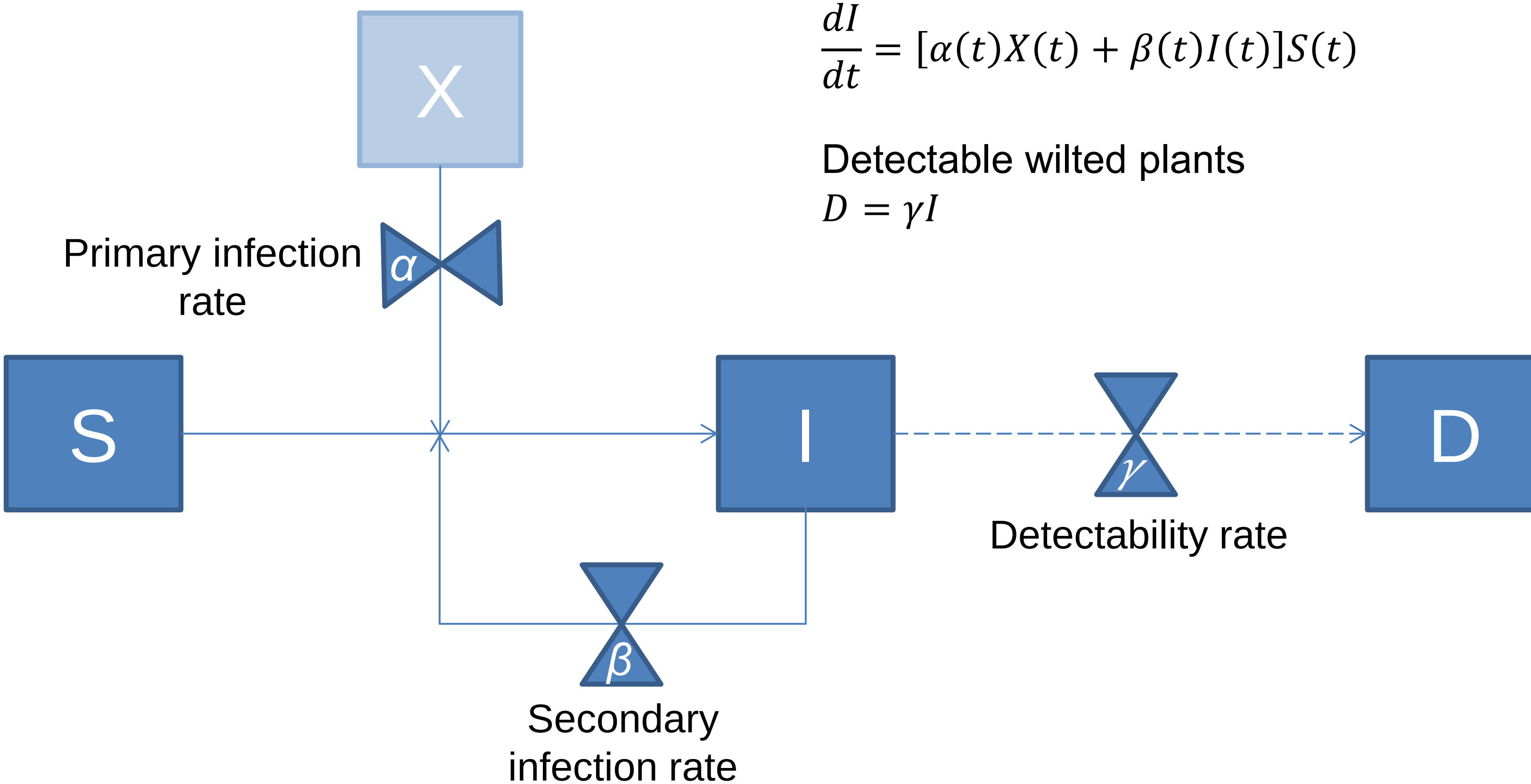
$$\frac{dS}{dt} = -[\alpha(t)X(t) + \beta(t)I(t)]S(t)$$

Infected plants

$$\frac{dI}{dt} = [\alpha(t)X(t) + \beta(t)I(t)]S(t)$$

Detectable wilted plants

$$D = \gamma I$$

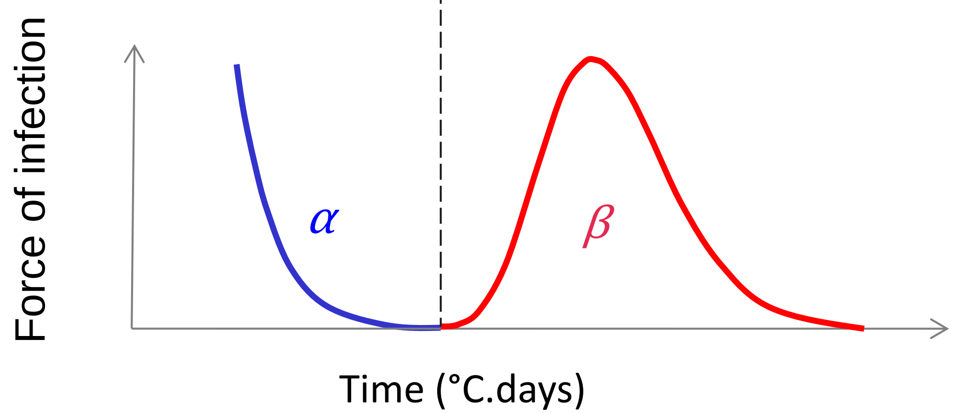


Motisi et al. (2013)

Derivation of the model

Primary infection rate
$\alpha(t) = \alpha_1 \exp(-\alpha_2 t)$

Secondary infection rate
$\beta(t) = \beta_1 \exp(-0.5[\log(t/\beta_3)/\beta_2]^2)$



Motisi et al. (2013)

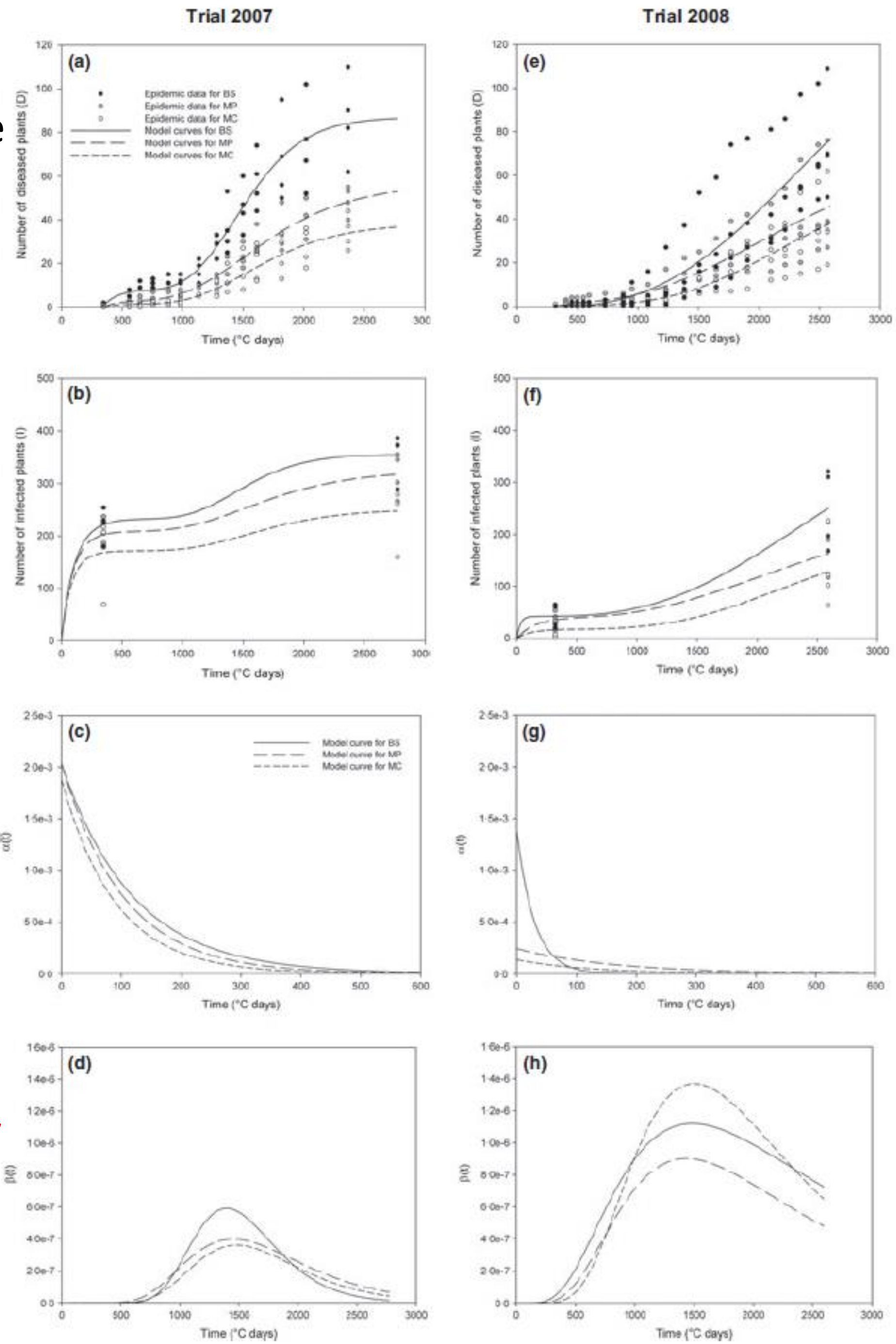
Results

Detectable wilted plants

Infected plants

Primary infection rate

Secondary infection rate



Control without mustard

Partial biofumigation

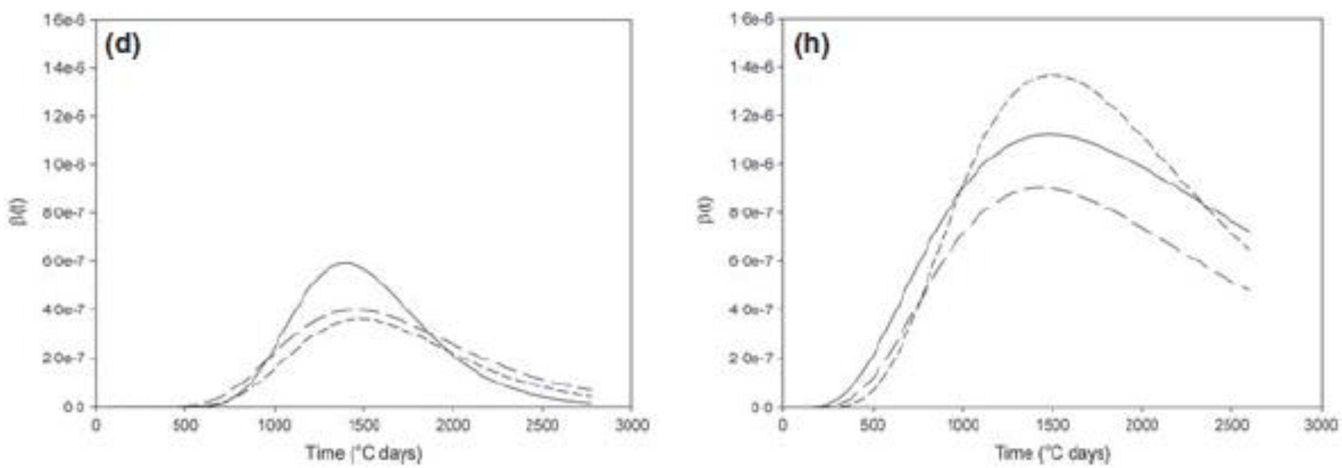
Complete biofumigation

- Biofumigation mostly **reduces primary infections**
- Biofumigation can **affect secondary infections** with a variable pattern

Motisi et al. (2013)

Discussion

- **Variability in efficiency** of biofumigation to control the rate of transmission of **secondary infection** can explain the variability observed among studies



Discussion

Small differences in the initial growth of inoculum

combined to the non linear multiplicative effects

of secondary infections

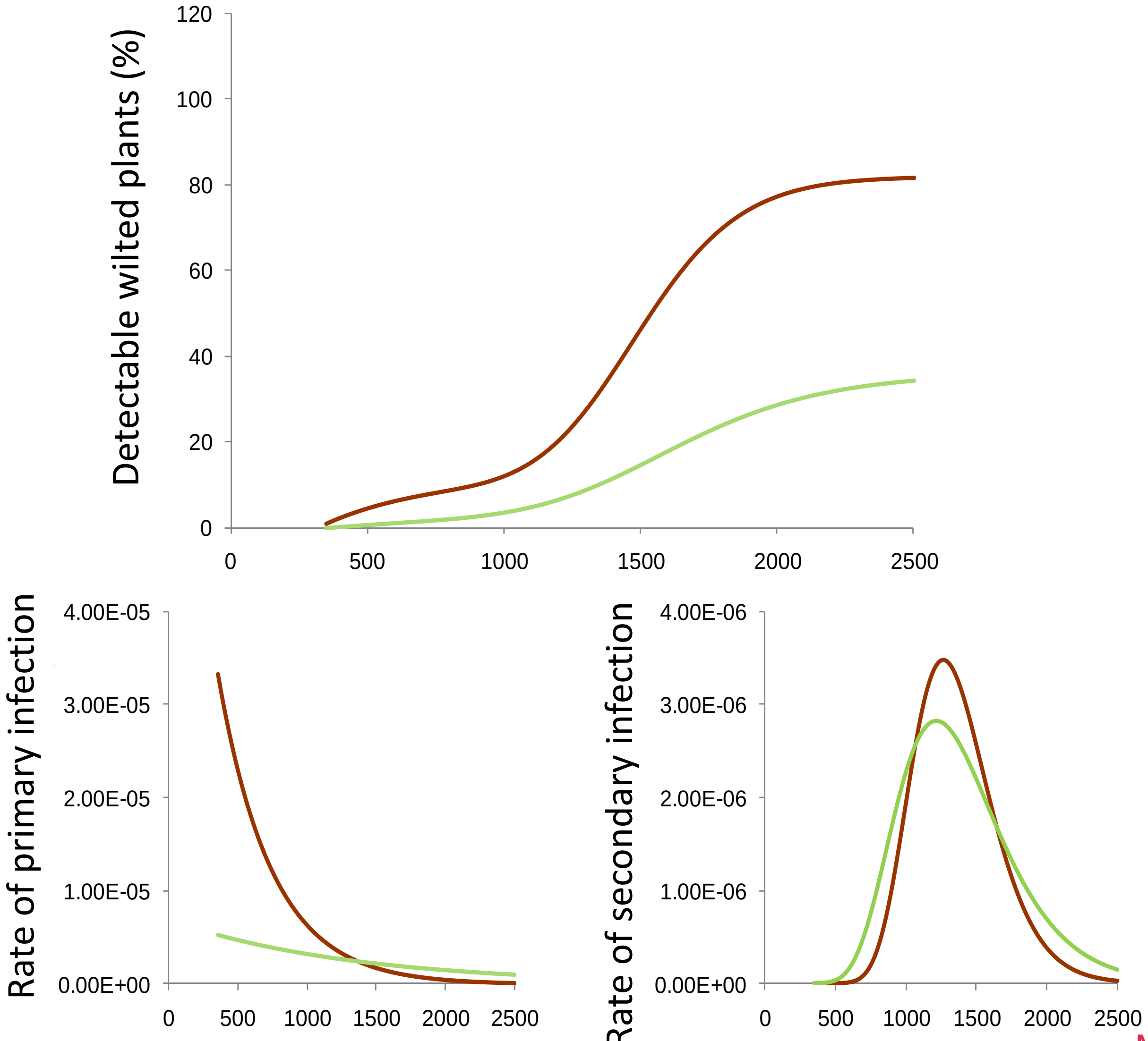
can lead to **great differences in the final size of disease foci**

(Kleczkowski et al., 1996)

Possible scenario

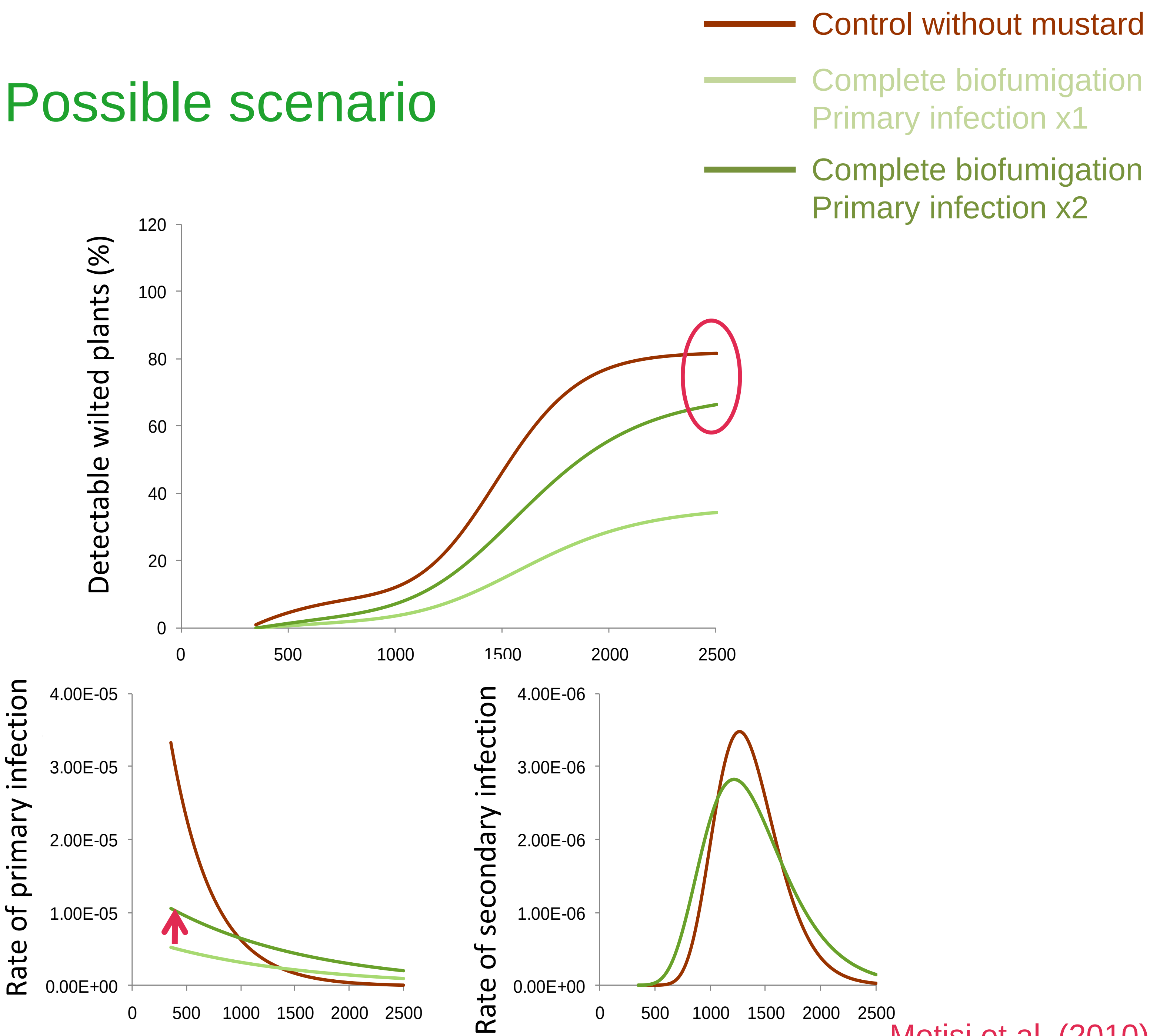
Control without mustard

Complete biofumigation
Primary infection x1



Motisi et al. (2010)

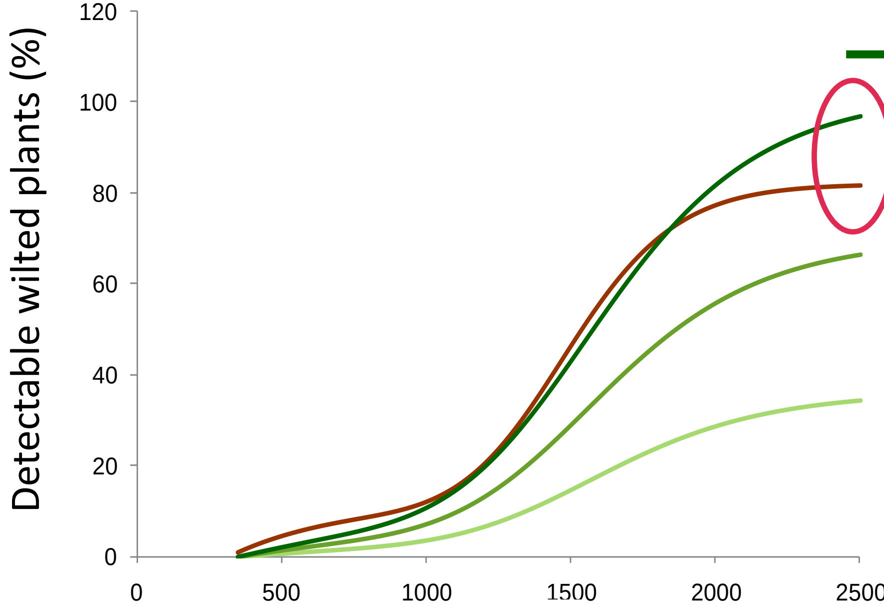
Possible scenario

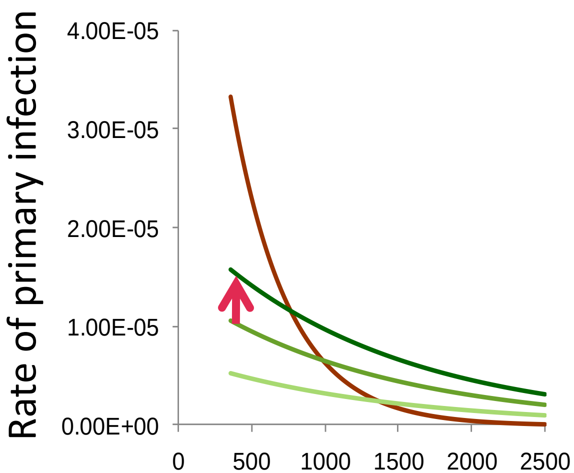


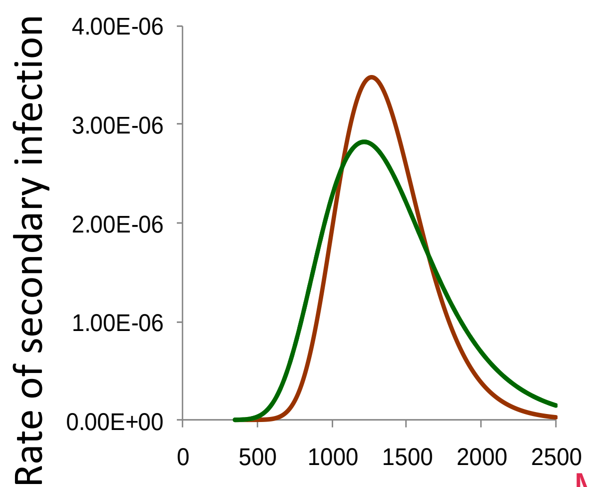
Motisi et al. (2010)

Possible scenario

Control without mustard
Complete biofumigation Primary infection x1
Complete biofumigation Primary infection x2
Complete biofumigation Primary infection x3







Motisi et al. (2010)

Conclusions on the first model

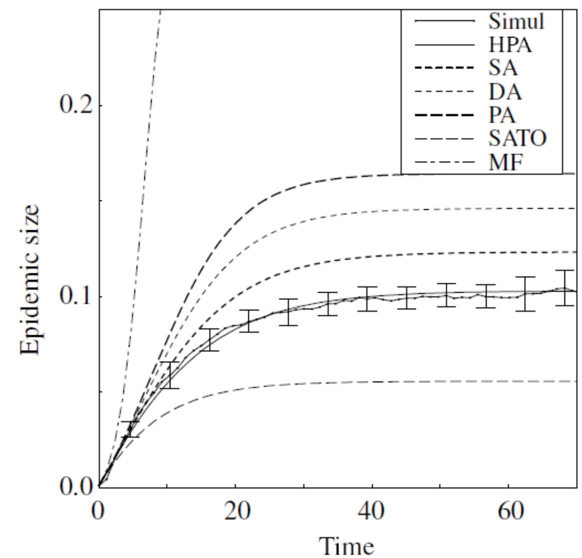
- First simple model
- Good insight into **epidemiological mechanisms** affected **by biofumigation**
- **Not allowed** when looking only at the final stage of disease development (harvest)
- Good efficiency of biofumigation depends on first efficacy on **primary infections**
- **Variability in efficiency of biofumigation on secondary infections** can provide variable results at the field scale

New avenues

How biofumigation affects the variability of *R. solani* epidemics ?

- Design of new modelling framework to predict the spatio-temporal spread of *R. solani*

- Why using **spatially explicit** models for this pathosystem ?
→ predict accurately epidemic development



Filipe & Gibson (2001)

- Use of **stochastic model** to predict the variability/uncertainty of epidemics

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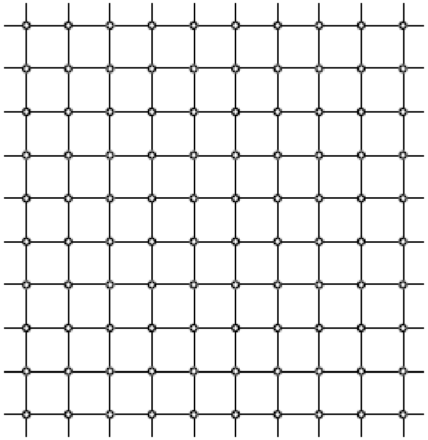
Structure of the stochastic spatially explicit model for forecasting

- Spatial individual-based model with stochastic spread of the pathogen
- Host plants are at vertices of a regular lattice
- SI model with primary and secondary infections



Stochastic infections

$$P(S_t \rightarrow I_{t+dt}) = [\alpha(t) + \beta(t) n_I].dt$$

Rate of primary infection

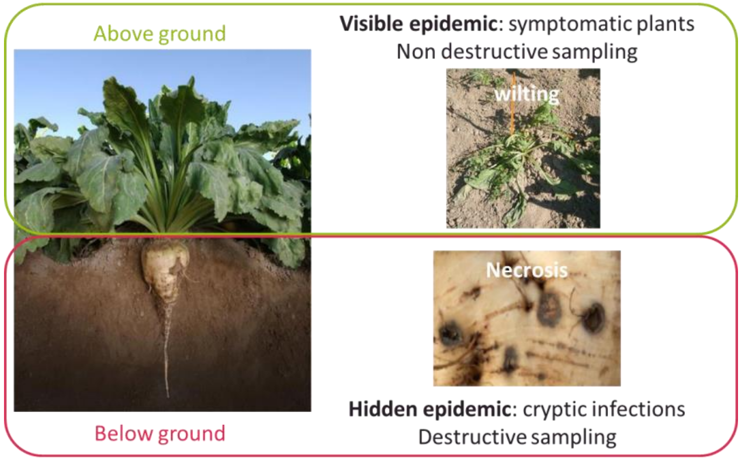
$$\begin{cases} \alpha(t) = \alpha_1 \exp(-\alpha_2 (t - t_0)) & \text{if } t_0 < t \\ \alpha(t) = 0 & \text{if } t_0 > t \end{cases}$$

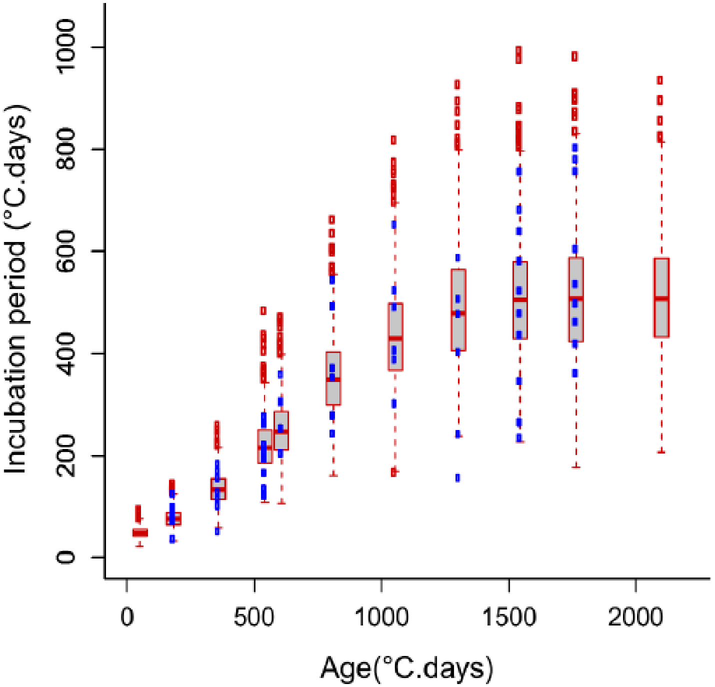
Rate of secondary infection

$$\beta = \beta_1 \exp(-0.5[\log(t / \beta_3) / \beta_2]^2)$$

Estimation of « spatial parameters » from temporal data

- Introduce a more realistic incubation period (time between hidden infection and detection of above-ground symptoms) for inferring epidemiological parameters
  - incubation period is age-dependent (Leclerc et al. 2014)

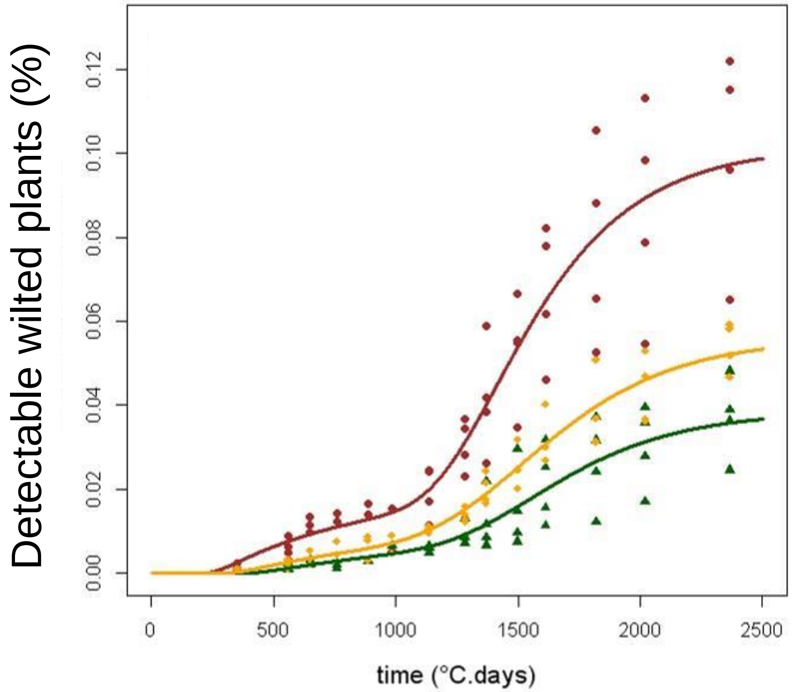


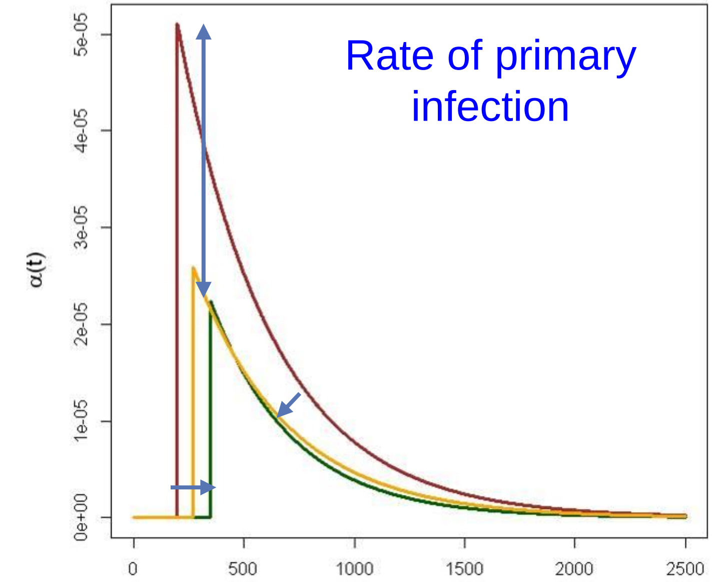


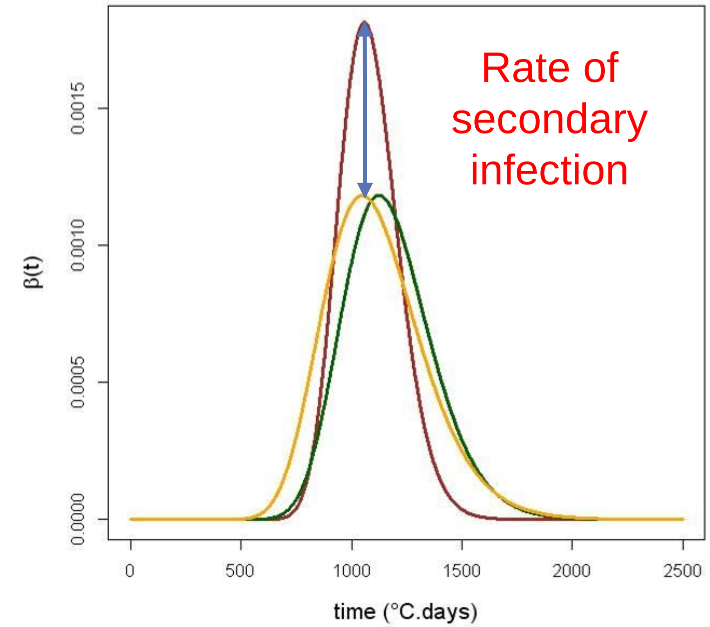
- Statistical inference of spatio-temporal parameters can be difficult and time consuming…
- Estimate spatial rates of infection using a semi-spatial model (Filipe et al., 2004)

Model fitting and estimated rates of infection

- Control without mustard
- Partial biofumigation
- Complete biofumigation



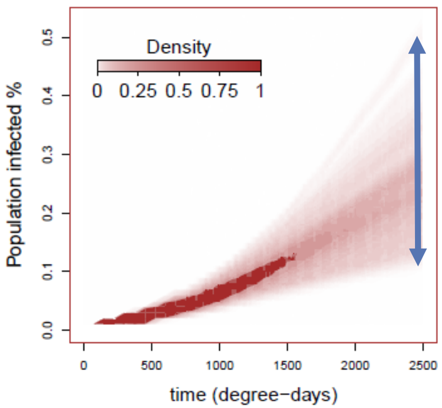




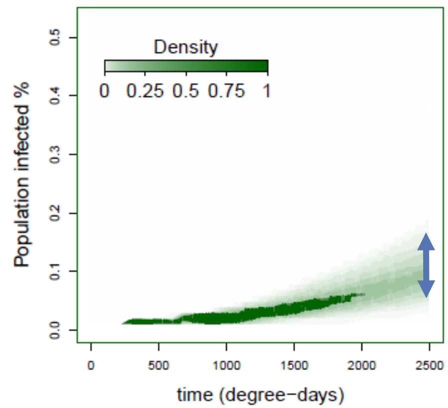
Biofumigation **reduced** rates of **primary** and **secondary** infection in this trial (2007)

Spatial model predictions

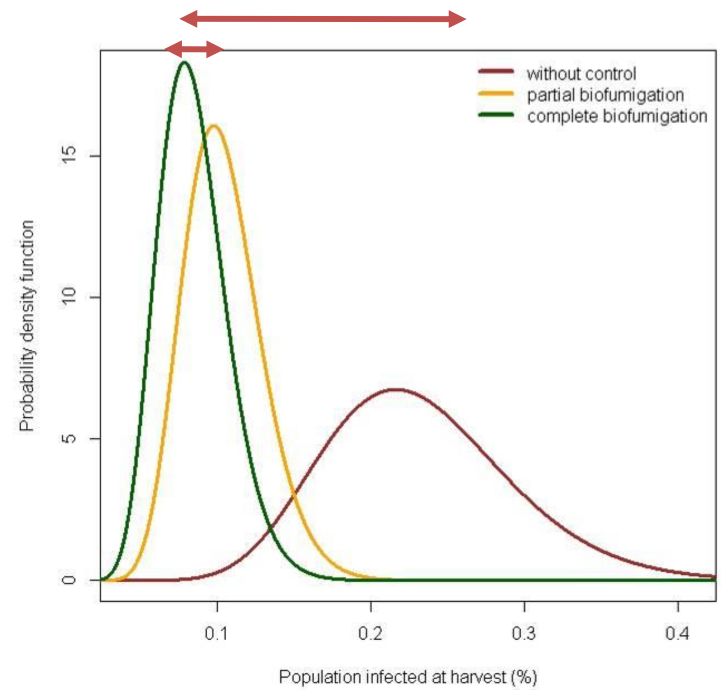
Control without mustard



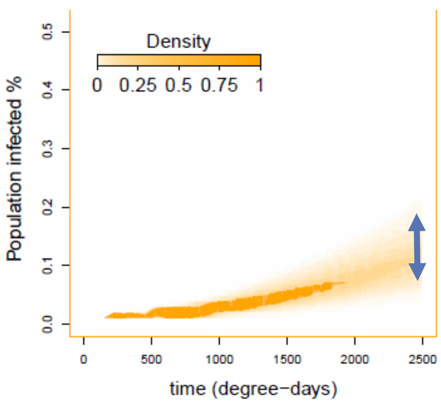
Complete biofumigation

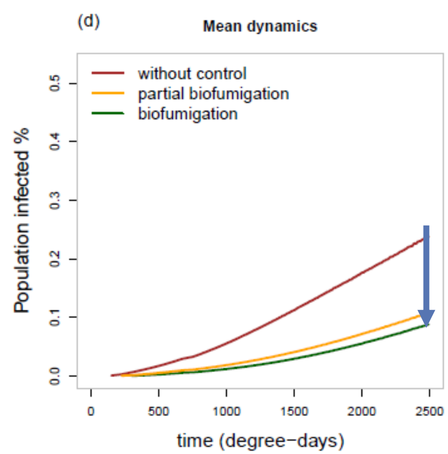


Distributions of infected plants at harvest (%)



Partial biofumigation





- Biofumigation provides partial control of epidemics
- Biofumigation seems to reduce the uncertainty in epidemic outcome
- Marginal differences between partial and complete biofumigation in 2007

Conclusions on the second model

- Analyses are consistent with previous results obtained with the temporal model but:
- We predict less primary infections and more secondary infections than in the previous study
  - New vision of epidemic : different disease progress curves
- Biofumigation seems to **reduce the uncertainty in epidemic outcome**
- Take these results with care
  - More statistical analyses are required to assess model fitting and conclude on the effects of treatments on epidemic development

Many thanks for your attention

Bibliography linked to this work

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Motisi N, Dore T, Lucas P, Montfort F, 2010. Dealing with the variability in biofumigation efficacy through an epidemiological framework. *Soil Biology & Biochemistry* **42**, 2044-57.

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Leclerc M, Dore T, Gilligan CA, Lucas P, Filipe JAN, 2014. Estimating the Delay between Host Infection and Disease (Incubation Period) and Assessing Its Significance to the Epidemiology of Plant Diseases. *Plos One* **9**, 15.